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FRACTAL BROWNIAN MODEL FOR SAR IMAGE ANALYSIS: EDGE DETECTION AND CLASSIFICATION ISSUES.

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ABSTRACT

Feature analysis is used to explore and improve SAR imagery and it is therefore of great relevance. In this paper, the Fractal Brownian Model for SAR image edge detection and classification is considered. Such a scheme has been formerly employed in analagous but different research fields (e.g., medical images) providing quite interesting results. First experimental results on SAR imagery are here presented and discussed showing analogies and differences with the latters.

***Index Terms:** Synthetic Aperture Radar (SAR), Fractal geometry, Edge-detection, Classification.*

MOTIVATIONS

Feature extraction is of primary interest in SAR (Synthetic Aperture Radar) data processing and applications. Unfortunately, as well known, SAR images are characterized by speckle noise which encumbers any data exploitment. In order to overcome such problems many techniques, appropriately tailored to the issue at hand, have been illustrated.

Recently, a novel geometry has been formulated: the fractal one [1,2].

Fractals do constitute a new and promising approach to image analysis and classification. In fact, fractal based techniques have been widely and successfully employed in different but analagous fields as for instance medical imaging [3]. Lately, their application in SAR imagery analysis attracted some interest (although fractals have not always explicitely accounted) [4,5]. Notwithstanding their application in SAR image context calls for further work in order to fully exploit their potentials.

Within such framework a key point arises: efficient estimation of fractal dimension D. As matter of fact it may drastically hamper time efficiency [3]. Hence, for our purposes, we are concerned with fractal techniques which should be fast and accurate (in terms of more classical schemes).

A popular and interesting approach is the one relying on the Fractal Brownian Model (FBM), i.e. the Wiener stochastic process extended to the fractal domain [2].

In this paper we present and discuss former fractal model within SAR imaging context therefore showing analogies and differences with some others imaging feature extraction applications [3,6,7].

The paper is organized as follows: first we outline the FBM, then we describe the employed method and finally we present some first results. Some conclusions and recommendations for future work end this paper.

FRACTAL BROWNIAN MODEL

First of all, we recall that a set whose Hausdorff-Besicovitch dimension is greater than its topological dimension is recognized as fractal. Moreover, fractals are continuous but not differentiable and show a fine detailed structure at any (arbitrarily) small scale. We emphasize anyhow that fractalness holds for physical data set only on part of the observable data.

An important fractal feature is their correlation over different scales of magnification; accordingly self-similarity or self-affinity properties are invoked [1,2]. Furthermore, fractals can be either determistic or stochastic.

Because of the fact that many natural phenomena have been explained in terms of fractal models this field has gained more and more interest. Among them the Fractal Brownian Model is a very popular and effective one.

The Fractal Brownian Model is a random self-affine fractal which can be also thought as an extension of the classical Wiener process whenever the parameter H is no more constrained to be equal to 1/2 but differently lies within the range 0,1 [1,2]. Persistent behaviour is implied when the Hurst exponent H is greater than 1/2, whereas an anti-persistent random process is modelled when H is smaller than 1/2 [2].

Namely, let $I(x,r)$ to be the image and x and r the azimuth and range coordinates, we have accordingly:

$$Pr\left(\frac{I(x,r)-I(x+\Delta x,r+\Delta r)}{\left(\sqrt{\Delta x^2+\Delta r^2}\right)^H}<\delta\right)=F(\delta) \quad , \tag{1}$$

wherein Pr means probability, $F(\delta)$ is a cumulative distribution function (cdf) and H is referred as the Hurst exponent and is related to the fractal dimension D. In the case at hand (image points defined by two coordinates) this relationship specifies as follows [2]:

$$D=3-H \quad . \tag{2}$$

Moreover, we emphasize that in eq.(1) the cdf $F(\delta)$ must be Levy stable [1], i.e. it must satisfy the following functional equation:

$$s_1F_1(\delta)+s_2F_2(\delta)=s_3F_3(\delta) \quad , \tag{3}$$

with the constraint,

$$s_1^D + s_2^D = s_3^D \quad . \tag{4}$$

Finally, it must be noted that eq.(2) leads to the classical Wiener process whenever $H=1/2$ and $F(\delta)$ stems from a zero-mean, unit-variance gaussian [2].
Eq.(1) can be written in a more suitable (for our purposes) form, that is:

$$\log E\left[\left|I(x+\Delta x, r+\Delta r) - I(x,r)\right|\right] + \\ -H \log\left[\sqrt{\Delta x^2 + \Delta r^2}\right] = K \quad , \tag{5}$$

wherein E is for statistical mean and K is a constant which depends on the assumed cdf (see eq.(1)).

METHOD

Rationales of the employed sheme are very simple: edges fractal dimension is lower than 2 [3], therefore a D estimator intrinsically performs an edge detection. Moreover D value is meant to be a classifier discriminator [3-7]. In fact, the fractal dimension tends to be uniform over a single class [3].
From previous discussion stems the important item of fractal dimension estimation. Among different procedures we have selected the spatial one, commonly called *fractal plot* whose essential rationale is given by eq.(5).
Basically a scatterplot of $\log E\left[|\Delta I|\right]$ vs. $\log \Delta d$ (see eq.(5)) must be drawn for any investigating window centered over the image pixel whose D has to be estimated. A linear regression among such a data measures the Hurst exponent and therefore D [2]. Upper and lower scale limits are intrinsically defined by a linearity test [8].
Some more comments are appropriate. First of all, we note that Δd is not meant to be integer as well as in the original Pentland approach [7] and therefore differently to Ref.[3]. Then, we stress that, with respect to Ref.[3], time efficiency has been improved. In fact, when the window size has been chosen, an original program creates a distance map that is used throughout the subsequent estimating procedure in order to speed it up. Such a strategy allows to examine a 128x128 pixel image by a 3x3 sliding window in a time of order of 10 sec instead of more than 1h[1].
Finally, we note that previous CPU time must be considered for reference only, because computer technology is already willing to significantly speed former computational time up: both employing sequential machine and parallel architecture.

RESULTS

We applied former fractal method to actual SAR imagery. The SAR image used for our first investigations was collected over Matera test site under the SAR-580 Italian campaign. In fig.1 is shown the corresponding multilook intensity image (256 grey-levels). We recognize in the image, different agricultural fields, some roads as well as a certain number of corner reflectors displayed for calibration purposes.
The procedure previously outlined has been employed in order to generate the fractal map shown under fig.2. A 5x5 sliding window has been used and the grey-levels are proportional to the fractal dimension D; we note that that the detected edges are darker as predicted by the model. A thresholded image is finally shown in fig.3. Subsequent procedures are usually employed in order to *clean* the thresholded image and to connect broken edges [9]. They are not here applied since not fundamentally relevant for the main scopes of this paper.
A comment about these results is now due.
First of all, we note that most of the edges within the image have been automatically revealed by the fractal-based procedure, henceforth encouraging use of this methodology in order to perfom a SAR image edge detection.
On the contrary we underline that the only use of the fractal dimension is by no means an efficient fractal discriminators among natural classes. Therefore the sole D estimation is generally not able to perform SAR image classification as well demonstrated in other fields [6].
In particular, a feature classification vector may be suitably considered when classification issue is in order. It is straightforward that estimation of K (see eq.(5)) can improve classification accuracy at very limited additional computational expenses. In addition, lacunarity [6] of the image can also improve classification results; noting, anyhow, that patterns with the same fractal dimension and lacunarity may appear quite different. Therefore, use of multifractals as well as non-isotropic approaches can be furtherly taken into account [10,11]. As important drawback, it must be stressed that estimation of latter fractal features is very time consuming.
Let us turn back our attention on the edge detection issue, now.
Fractal scheme accomplished over one (or almost) look image has yielded poor results whereas, as already stated, use of multi-look images provided much better edge detection. This result is a pretty one and beyond brute force experimentations pose a theoretical problem: Does fractalness hold for SAR imagery?
Pentland proves that a sufficient test can be performed estimating D over an image and its averaged down replicas, whenever such a measure is stable the test is passed [7]. Of course, D stability is of fundamental importance in classification issue whereas has minor impact on the edge detection issue, provided a discrimator index (measured among desired and undesidered features) is guaranteed [7]. Stated in other words, whenever fractal edge detection scheme is in order, we need that the edge detector discriminator is stable among different magnifications.
A conjecture is meant to be true: fractalness is exhibited only by multilook SAR imagery. A more detailed measure of such occurrence is obviously given by the speckle nature; we note anyhow that the FBM edge detection scheme does not require its explicit knowledge (see eq.(5)). Further investigations on the field are certainly appropriate and we mean to use simulated images [12], too.

CONCLUSIONS

Fractal Brownian Model for SAR image analysis has been inquired.
As a conclusion, we experimented that edge detection fractal scheme does provide poor results when applied on SAR single-look images, thus differently with medical ones. Actually pre-processed SAR images gives much better results.
Therefore such a fractal edge detection procedure yields good results at resolution expenses. We emphasize that such trade-off must be always paid in more traditional schemes in order to regularize the ill-posed problem at hand [13].
Finally analogies with classical application of fractal methods [6] have been recognized when classification is in order; that is fractal dimension estimation does not provide

[1] Test performed on a 6000-210 VAX-DIGITAL computer, normal task conditions.

by itself a sufficient criteria. Therefore, employment of some additional fractal features must be considered as future work; keeping in mind that benefits must be also measured in terms of computational time.

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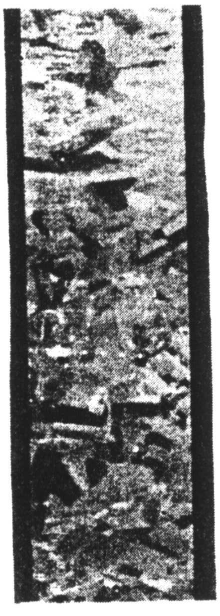

Fig.1: SAR image relevant to the Matera, Italy test site acquired under the SAR-580 Italian campaign mission.

Fig.2: Fractal map generated by means of the Fractal Brownian Model applied on the SAR image shown in Fig.1.

Fig.3: Thresholded binary image of image depicted under Fig.2.

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